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DEVELOPING A SCALE TO MEASURE A FOOTBALL PLAYER'S TRANSFER SCORE

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ABSTRACT

The aim of this study is to develop a scale that demonstrates the transfer score of a football player, with the help of metrics generated through network science. Six matches played Turkish National Football Team in the 2014 World Cup Qualifiers were analyzed with e-analysis soccer program. To obtain the network of the matches and the measurements of networks we used the open-source program Gephi. By taking into consideration the correlations between 11 network metrics, factor analysis was performed, and factor loadings were obtained. To determine the transfer score, as a measure of centralization: degree, weighted-degree and betweenness-centrality, and as a measure of contravention: eccentricity, 4 variables were defined. As a result of factor analysis, three variables were combined into a single component. The variance explanation value was found to be 90.611%, the internal consistency criterion was 0.66 and the transfer score value was calculated using the squares of factor loadings. The scale we developed will be able to determine the transfer value of a player, as well as the changes in the player's performance over time.

Contribution/Originality: This study contributes in the existing literature with a new scale that can be used as a support tool in the existing transfer system. With the development of such scale, the transfer score of soccer players will be determined and the change of their performance over time could be observed.

1. INTRODUCTION

In the middle of 2018, it would not be wrong to say that football clubs in our country are in debt. There can be a variety of reasons for this, and it can be said that transfers are one of them. Today, it is known that in the football, very large amounts of money are exchanged, especially during the transfer windows. Statistics are now being used to measure performance in a variety of sports, including football. On the other hand, in recent years besides statistics, data science and network science have begun to be used in such analyzes. However, whatever the developments are, the decision to transfer in the football market is still based on subjective views rather than on objective data.

In recent years, network science, one of the most important areas of applied physics and mathematics, has been used to analyze the interactions of units within the framework of complexity theory. Network science can be used not only for footballers but also for measuring the performances of both teams and players, focusing on interactions between them and using pass nets.

We cannot imagine football being independent of technological developments. Technology will change the subjective perspective on football and will bring an objective basis to this sport. Nowadays, we can say that newly developing fields such as data science and network science will find a great use for football. VAR (video assistant referee) systems, which have been under development since the beginning of the year 2010 and ensure that the right decisions are taken in games, are the clearest indicators of this.

PhD dissertations have begun to be written on the application of network science to football (Barghi, 2015). If the correct data are interpreted using the right technology, the quality of the football will be positively affected. The on-line determination of football players' positions on the field by deep learning (Visibelli, 2018) and modeling of the data obtained on-line during the matches by machine learning are not possible only in science-fiction films anymore (Clemens, 2018).

But in spite of all these technological developments and contributions, there is still a huge research gap for the applications of network science in football. In the leagues very unsuccessful results can be gotten with football players whose transfer prices are very high. Valid system in today's football market, where transfer values are subjectively determined, is highly risky for clubs, where they can face financial distress. For this reason, there is a need for objective support systems that can help in the negotiations made during the transfer periods. We believe that, the scale we propose in this article, which determines the transfer value by utilizing the performance of a football player during the course of a season on the pass networks, can provide this support.

Every year in the Turkish football market there is an incredible amount of money exchange. For example, according to the Turkey Football Federation's statement, in the 2017-2018 season, by the end of February the payments made to players' managers worth million Euros (Sabah Sports, 2018). However, it is possible to mention that neither the legal framework nor scientific approaches are adequately used for these large amounts of money exchange in the football market. Moreover, these shortcomings are not just specific to Turkey. It is stated by some authors that the inadequacies of FIFA's regulations make it possible for footballers and their clubs to be exploited (Akşar, 2015).

There are about 20 managers in the world who control the management market. The football management is not a very old profession, and from time to time there are rumors that this institution will be abolished (Cumhuriyet Sports, 2010). Everyone knows that such a thing is not possible in the short term. Some argue that, such an institution is necessary. "Today, we need to protect football players' legal and financial rights against their clubs, and/or we need a proper and supervisory management system for protection of club interests against footballers." The size of the sector reaching a billion Euros makes such an institution compulsory (Akşar, 2015).

Managers receive a commission of between 10% and 20% on each contract. Even in 2016, these commissions were about 6 million 600 thousand Euros (Fanatik, 2016). In addition, the vast majority of transfers in our country are carried out by "pirate" managers. To understand what is going on during the transfer window, we should pay attention to the words published in media of an ex-executive of one of the three major teams in Turkey: "I was carrying out the transfers ... I was talking to the footballers personally ... they were doing the negotiations themselves ... I mean they were not letting the managers involve. So they prevent the artificial swelling in the fee of the footballers, and possible abuses ... Even the commission to be given to the managers was left in the club (Türker, 2016). To sum up; as Cemal Ersen said, "But we have to understand the fact that the biggest problem of Turkish football is the managers: there is a mind-set for years, which is basically ripping off the clubs. Managers, cooperating with executives, trying to sell above market value, marketing fake star candidates, doing tricks to evade taxes, cause this problem. If you are questioning why the clubs are bankrupting, you will first sincerely step in to

solve the manager problem" (Ersen, 2018). We finish this section with a statement said for the England League, "Football club owners have to understand that football is a sport where managers gamble with their money" (Arsenal Review, 2009). Based on this perspective, in this article we will try to develop a scale that demonstrates the transfer score of a soccer player at the end of each match and on average at the end of a league season, by taking average of the metrics obtained from network science. Shortly, in this article firstly, we will obtain various measures from a football player's pass nets; then we will try to develop a scale that measures the transfer score of the football player. With the development of such a scale, not only the transfer score of a soccer player will be determined, but also the change in his performance over time could be observed. In addition, with the help of this scale, it will be possible to observe the performance of a team on a single point in time, as well as its change in its performance over time. By applying the network science to pass nets in football, the main contribution of this paper is to develop a scale to determine the transfer value of a football player. In other words, we believe that our article may contribute to the literature with a new scale that can be used as a support tool in the existing transfer system.

1.1. Football and Data

In this section, we will try to briefly summarize what is the use of data in the football nowadays. Today, professional statistical analysis firms such as ProZone and Opta provide data to the football clubs and to their technical directors to develop team strategies and to monitor their players (Cintia *et al.*, 2018).

In Turkey Super League, TFF League 1st and TFF League 2nd get data from companies such as Sentio, Instat and Wyscout for coaches and analysts in order to develop strategies and monitor their players. It is also a fact that such programs are expensive, and as the league category scales down, buying and using these programs become difficult, thus it turns out to be tough to track players and to form a strategy. Match Analysis Coaches are purchasing data from a number of sites (Matchstudy/Match-Ball, etc.) with their own resources or are trying to develop strategies for the team by hiring a number of programs.

1.2. Opta

Opta is a visionary company, which offers detailed live or past matches' data to better the best sports experiences. Opta is the world's leading supplier of detailed sports data. Having a 20-year history, Opta collects, analyzes and distributes data and content to sports clients. It serves customers worldwide in publishing, media, betting, professional fans, sponsorship and brand activation areas. At Opta, the process begins with data and is carried out by specialized data analysts at centers around the world, supported by stadium analysts. Opta's biggest advantage is to provide solutions to different customer needs, technologies and platforms. The pyramid system that introduces the operation of Opta is shown in Figure 1.

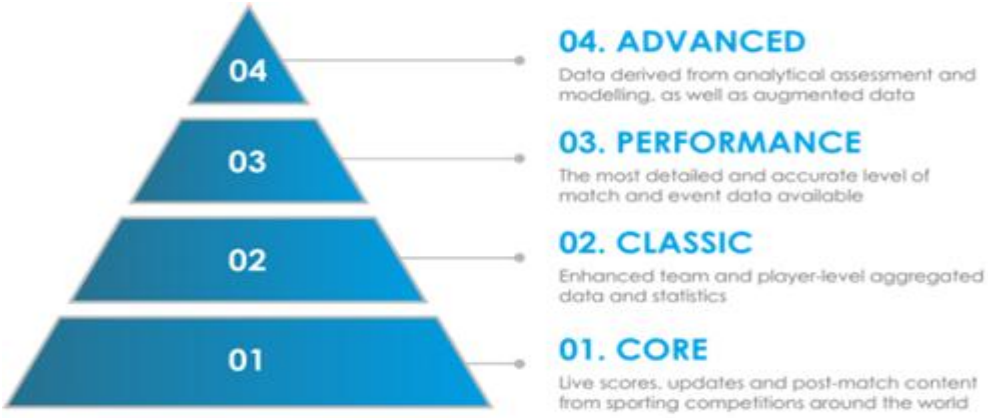

Figure-1. Opta Data Layers The Opta Difference (2018).
Source: https://www.optasports.com/about/the-opta-difference/.

1.3. Wyscout

Wyscout works with membership system. Subscription option, that includes unlimited access to videos of one country, unlimited data and statistics and transfer tool costs 148 Euros per month. For this charge, the Wyscout provides all kinds of data to the manager, coach, analyst and scout in the competition. It offers video, data, statistics and a number of tools for professionals. There are versions that can be run on desktop computers, tablets and mobile phones. It serves more than 1,200 countries. Scored and defeated goals include goals scored, offense, defensive tactics, counterattacks, corner positions, free throw positions, penalties, throws, offside positions, fouls. For the players, all the actions in the game such as positive and negative types of passes, positive and negative shots, playing time, goals and assists, positions missed, cards seen, fouls made and won are included Figure 2.

Figure-2. A wyscout screenshot Wyscout The Professional platform (2018).

Source: https://wyscout.com/

1.4. Transfermarkt

Transfermarkt is a company that provides the most recent transfers that take place primarily at national and international level. Transfermarkt provides the values of these transfers with various statistics, the ongoing and ended contracts signed with the players, the managers and the technical directors. The company also provides data on national and international competition results, competition statistics and player performances Figure 3.

Figure-3. A screenshot from Transfermarkt website Transfermarkt (2018).
Source: https://www.transfermarkt.com.tr/

1.5. .Football and Network Science Studies

We can analyze a soccer game with a network approach, when we think of a team's footballers as nodes and directed edges as passes. At the end of every soccer game, a network comes out of the soccer players' passes. We give this network the name "pass network". Network science provides a systematic framework for quantitative research of complex systems. It is thought that the network approach can successfully quantify the performance of each individual player and team (Duch *et al.*, 2010). Let's add that transfer values are important enough to affect the stock values of the team (March, 2014) and that various methods are used to estimate the value realized in the market (He, 2018). In addition to these, network patterns in different team sports have also been examined by being compared (Korte and Lames, 2018).

A study has shown that network evaluations were correlated with success rates and did successfully predict game results in FIFA World Cup 2014 and Italian Serie A 2013/2014 (Cintia *et al.*, 2018). There are many studies examine football transfer market via network approach (Lee *et al.*, 2015). A study in this framework revealed that the global football transfer market network is a small world network[1] of loosely connected hubs (Liu *et al.*, 2016; He, 2018).

On the other hand, there are signals that the pass networks are a small world network as well. For example, in a study, the Dutch football team's network was described as a small world network because the average distance between players (4.49) was short. Again, it was found that the clustering coefficient of this network is high (0.75) and the longest radius of the shortest pathways is 11 (Kooij *et al.*, 2009).

In the analysis of 380 matches played in the England Premier League in the 2012/2013 season, a significant difference (p=0.01) was found between the top ten teams and the bottom ten teams in terms of ball holding and short passes (Araya and Larkin, 2013). In a study that examined matches in the first and second halves is an network framework, the average intensity of the first halves were 0.48 and the second halves were 0.32 (Clemente *et al.*, 2016).

[1]Basic networks include random networks, small world networks and scale independent networks. A small world network is a network, in which the nodes in the network are not neighbors of each other and the majority of the nodes are accessible by fewer steps (bounces) by the other nodes.

Other recent studies tried to forecast match results (Arabzad *et al.*, 2014) and player transfer values via artificial neural networks (Dey *et al.*, 2017). In a study of 2014 World Cup, it was determined that the total number of links, network density, and the size of the cluster coefficients are related to a higher number of goals. Again, according to the same study, having high values of links between team players is associated with better team performance (Clemente *et al.*, 2015).

However, the results are not always positive. In another study, there were very low correlations between classical performance variables such as goals and shots and variables such as network density, total number of links and cluster coefficients. The findings of this study indicate that there is a positive and moderate relationship only between ball holding percentage and network measures (Clemente and Martins, 2017).

1.6. Network Measures

The network measurements that can be used in the football (Barabási, 2018) can generally be grouped into two:

- Network measures for the overall match.
- Measurements for Soccer players (in network terminology: network measurements of nodes).

Let's just add that some of the measures may be related to both the players and the overall match in general. Some measures such as density, radius can only be calculated for the network (match) in general.

The density is calculated as the ratio of the number of connections in a network to the maximum number of connections. A node's eccentricity is the greatest distance of a node to any node in the network. The networks eccentricity is the mean of eccentricity of all the nodes. The diameter, which is the calculated for the network, is the longest of the shortest paths between nodes. In terms of football, it shows how close or far the players are to each other in a pass network. It is also related to the eccentricity of the radius. The radius can be considered as the maximum eccentricity.

Degree centrality measures how many passes a particular player receives or gives to and from other players. High degree centrality of a player shows that said player is effective in the game. Eigenvalue centrality gives us the sum of the connections to other nodes, weighted roughly by the center of a node, and the effect of a player on the network. Weighted degree centrality corrects the weights of the classical degree of centroid measure using a reducing factor. As the distance from the equal weights increases, the reduction increases (Newman, 2001).

The centrality of betweenness measures the extent to which a node is in the path between the other nodes in the network. Closeness centrality determines how easy it is to reach a particular player on the team. The node with the lowest degree of closeness can be regarded as the most central node. PageRank is a measure developed by Google's founders, Sergei Brin and Larry Page, to measure the importance of web pages. For nodes with significant connections, nodes with many connections, have a higher PageRank value. If a footballer has more connections with footballers with significant connections, he has a higher PageRank value.

The clustering coefficient can be calculated for both the nodes and the general network. The clustering coefficient indicates how connected a neighbor is to a given node. If the cluster coefficient of any node is $C_i = 0$, we can say that none of the neighboring nodes are in connection with each other. When $C_i = 1$, neighbors are fully connected with each other. In short, the more connected a nodes neighbors are, the greater the cluster coefficient of that node.

2. METHODS

2.1. Developing a Scale to Measure the Transfer Score of a Football Player

When a football player's transfer value is measured, two basic metrics come out. While trying to determine the transfer value of a football player:

- The metrics obtained during the performance of the footballer or

- The non-performance metrics of the footballer can be used.

Percentage of successful passes, ratio the time he played during one league to the total time, number of assists, number of goals can be used to determine the transfer value of a football player. In this research, the metrics we produce from the passes of a match is also within this group. On the other hand, the footballer's age, his "iconic" (Arsenal Review, 2009) value- in terms of his popularity on media- benefits that the club has made for his commercial activities. We should also add that even the speed of the wind in a significant game can affect the transfer value. In summary, we should be aware that this value can be affected by a large number of variables, but in the real world we are not be able to use all of them, because it will cause problems both in terms of measurement and modeling.

We would like to emphasize that it this article sometimes we mention “transfer value”. In this research we try to explain how to determine the "transfer score" of a player at the end of a soccer season- in other words his grade in the range of 0-100. Then, in another study, it can be studied on how to correlate these scores with monetary transfer values.

In this study, we focused on performance measures such as game network scores, goals and assists, and Non-performance variables such as age, iconic value were not included in determining the transfer score. However, how non-performance variables can be added to the framework, may also be a topic for a further study.

We used for each match 11 network measures Figure 5 along with goals and assist values of the players. Subjectively we used 60% of the net weights and 40% of the goal/assists values in our scale. Those who will follow this approach can change these percentages according to their own subjective weights.

In this study, the factor loadings were determined from 6 matches of Turkish National Team and the transfer scores of the footballers were obtained. In fact, in order to be able to determine transfer scores at the end of a season, factor loadings must be determined from previous season matches. In summary, in reality, the process needs to take place as follows:

- Determination of the factor loadings by the measurements obtained from the networks of the previous season matches,
- Determining the transfer scores by using the factor loadings obtained from the new season's matches, goals, assists and the previous season's factor loadings.

The following steps were taken in determining the transfer scores.

2.2. Preparing the Data

In the preparation of the data, firstly the Excel pass files obtained from the images of each game were processed in the open-source Gephi program and the networks of the matches and the measurements of these networks were obtained. We like to share the network drawing from the Turkey-Estonia World Cup 2014 qualifying match, played on 09/11/2012 and resulting 3-0 Turkey's victory, see Figure 4 and the resulting network measurements see Figure 5.

3. RESULTS

3.1. Calculation of Factor Loadings by Factor Analysis

In fact, in such an application to conduct factor analysis data obtained from all the matches of the team in one season – as it is given in Figure 5 supposed to be used (Yurdabakan and Çüm, 2017). However, using a whole season’s data is challenging, it requires a lot time and effort, so we have chosen to make a sample using the data (figures) from six matches given in appendix to conduct factor analysis. In our example we will use the data of these six games as the previous season's data.

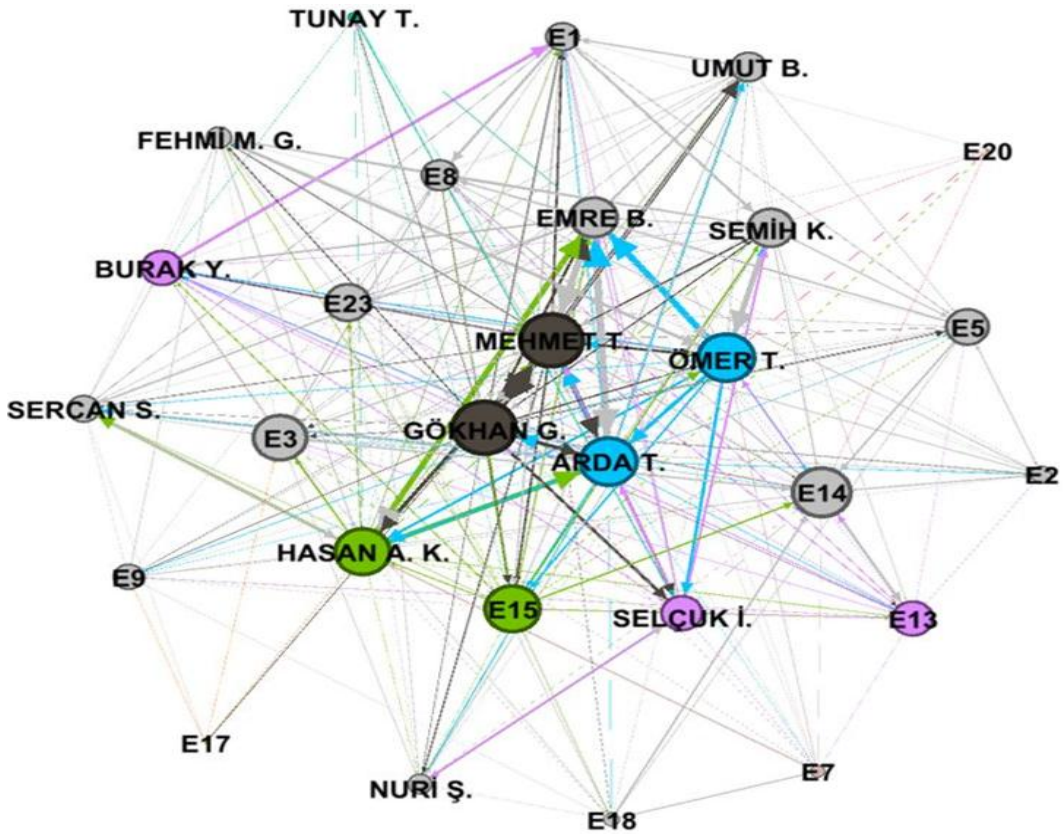

Figure-4. Turkey-Estonia qualifying match of the 2014 World Cup Network.

ID	LABEL	IN-DEGREE	OUT-DEGREE	DEGREE	WEIGHTED IN-DEGREE	WEIGHTED OUT-DEGREE	WEIGHTED DEGREE	ECCENTRİCİTY	CLOSENESS CENTRALITY	HARMONIC CLOSENESS CENTRALITY	BETWEENNESS CENTRALITY	PAGERANK
T17	BURAK Y.	15	15	30	37	38	75	2	0.692307692	0.777777778	9.211051345	0.038673713
T5	EMRE B.	18	16	34	96	95	191	2	0.710526316	0.796296296	14.99668691	0.04492767
T3	HASAN A. K.	22	17	39	74	74	148	2	0.72972973	0.814814815	28.39061871	0.05633647
T15	MEHMET T.	23	21	44	116	116	232	2	0.818181818	0.888888889	46.1557516	0.05891858
T9	UMUT B.	12	14	26	37	36	73	2	0.675	0.759259259	2.436602695	0.031317595
T21	ÖMER T.	22	18	40	80	80	160	2	0.75	0.833333333	29.51691488	0.058043333
T14	ARDA T.	18	22	40	96	96	192	2	0.84375	0.907407407	18.09399238	0.045504713
T7	GÖKHAN G.	22	22	44	92	92	184	2	0.84375	0.907407407	33.65629999	0.054547169
E23	E23	16	16	32	25	25	50	2	0.710526316	0.796296296	16.30816257	0.040614449
E13	E13	16	14	30	32	32	64	2	0.675	0.759259259	8.347052698	0.040641056
E9	E9	12	11	23	15	15	30	2	0.627906977	0.703703704	8.622982689	0.030064605
T4	SEMİH K.	17	16	33	53	53	106	2	0.710526316	0.796296296	14.35736892	0.044414186
E5	E5	16	15	31	31	31	62	2	0.692307692	0.777777778	7.805514193	0.040077965
T12	FEHMİ M. G.	12	8	20	24	24	48	3	0.574468085	0.641975309	3.302820279	0.030635248
E3	E3	19	19	38	36	36	72	2	0.771428571	0.851851852	28.72313656	0.048864265
E8	E8	12	15	27	31	31	62	2	0.692307692	0.777777778	6.345128337	0.031491036
E15	E15	18	21	39	42	42	84	2	0.818181818	0.888888889	28.72240717	0.044643041
E14	E14	19	22	41	46	46	92	2	0.84375	0.907407407	34.28566409	0.050084759
E1	E1	12	13	25	40	40	80	2	0.658536585	0.740740741	9.170510922	0.029834881
T23	SERCAN S.	10	14	24	32	32	64	2	0.675	0.759259259	8.097439957	0.027874807
E17	E17	2	3	5	3	3	6	3	0.5	0.537037037	0	0.006342458
E2	E2	8	9	17	16	17	33	3	0.586956522	0.660493827	0.91945179	0.021288887
E18	E18	8	6	14	12	13	25	3	0.551020408	0.604938272	1.597161172	0.020587681
E7	E7	7	6	13	10	10	20	3	0.551020408	0.604938272	1.112373737	0.018711608
T8	SELÇUK İ.	14	16	30	50	49	99	2	0.710526316	0.796296296	11.50027601	0.036340635
T11	TUNAY T.	5	7	12	9	9	18	2	0.574468085	0.62962963	0.518686869	0.014222391
E20	E20	3	3	6	3	3	6	3	0.509433962	0.543209877	0.16025641	0.008397879
T10	NURİ Ş.	10	9	19	21	21	42	2	0.6	0.666666667	4.645687135	0.02659892

Figure-5. Network Metrics of the Turkey-Estonia World Cup 2014 Qualifying Match.

In the correlation matrix in Table 1, it is seen that there are negative correlations between ECCENTRICITY and other variables. This shows that this variable differs from other centrality measures and as its name suggested it is an independent irregularity variable.

Table-1. Correlation Matrix.

	In_Degree	Out_Degree	Degree	Weighted_ In_Degree	Weighted_ Out_Degree	Weighted_ Degree	Eccentricity	Closeness_ Centrality	Harmonic_ Closeness_ Centrality	Betweenness_ Centrality	Pagerank
In_Degree	1										
Out_Degree	0,926	1									
Degree	0,983	0,98	1								
Weighted_ In_Degree	0,869	0,876	0,889	1							
Weighted_ Out_Degree	0,869	0,876	0,889	1	1						
Weighted_ Degree	0,869	0,876	0,889	1	1	1					
Eccentricity	-0,289	-0,344	-0,321	-0,191	-0,191	-0,191	1				
Closeness_ Centrality	0,05	0,072	0,061	-0,009	-0,008	-0,008	-0,821	1			
Harmonic_ Closeness_ Centrality	0,925	0,999	0,978	0,87	0,87	0,87	-0,351	0,064	1		
Betweenness_ Centrality	0,853	0,848	0,867	0,821	0,821	0,821	-0,26	0,061	0,845	1	
Pagerank	0,997	0,927	0,982	0,875	0,875	0,875	-0,26	0,03	0,926	0,856	1

Thus, in determining the transfer score, 4 variables were used. As measure of centrality: Degree, Weighted Degree and Betweenness Centrality variables Table 2 and on the other side, ECCENTRICITY. Factor analysis has been applied to see whether the three variables can be combined to form a centrality component or not and whether they have sub dimensions. Factor analysis applied by Principal Component Method is as follows;

Table-2. Correlation Matrix-2.

		Weighted_ Degree	Betweenness_ Centrality	Degree
Weighted_Degree	Pearson Correlation	1	,821**	,889**
	Sig. (1-tailed)		0	0
	Sum of Squares and Cross-products	130212,426	22878,5	27780,298
	Covariance	1587,956	279,006	338,784
	N	83	83	83
Betweenness_Centrality	Pearson Correlation	,821**	1	,867**
	Sig. (1-tailed)	0		0
	Sum of Squares and Cross-products	22878,5	5959,402	5794,97
	Covariance	279,006	72,676	70,67
	N	83	83	83
Degree	Pearson Correlation	,889**	,867**	1
	Sig. (1-tailed)	0	0	
	Sum of Squares and Cross-products	27780,298	5794,97	7500,222
	Covariance	338,784	70,67	91,466
	N	83	83	83

**. Correlation is significant at the 0,01 Level (1-tailed).

As a starting point of factor analysis, first the correlation matrix need to be examined, to observe the correlational relationship between the variables (Nakip, 2013). The correlation coefficients between the absolute values of the variables must be at least 0.30. If the correlation coefficients are lower than 0.30, the goal of reducing the size, which is the practical benefit of factor analysis, will cease to exist, as there are likely to be factors as many as the number of variables. Furthermore, high correlations between variables lead to multicollinearity[2] (Şencan, 2005) and singularity[3] problems (Şencan, 2005).

After examining the correlations between the variables with the help of the SPSS program, the Kaiser-Meyer-Olkin (KMO) was applied to test the appropriateness of the sample size to the factor analysis. KMO is an index showing the suitability for factor analysis. In general, the minimum KMO value is accepted 0.5 in many studies (Malhotra, 2004). In our study, KMO value was found 0.757 Table 3. Since KMO value was greater than the critical value, based on the assumption that the sample size is sufficient, factor analysis was conducted.

Table-3. KMO and Barlett's Test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0,757
Bartlett's Test of Sphericity	Approx. Chi-Sguare	240,817
	df	3
	Sig.	0

In the factor analysis, the Barlettsphericity test was applied to test the suitability of the variables. This test tests whether there is a relationship between the variables in the population (Nakip, 2013). The Barlettsphericity test gives a chi-square (x^2) statistical value. In this test, like in the other (x^2) tests, the significance value is measured

[2]Multicolineraity: Variables being highly related to each other in pair. (r>.90). It is also called multi linearity. It is the state, where a variable can be substituted by another one, because of their high similarity.

[3]Singularity: The correlation coefficient between the pair of variables is 1.0.

and if the significance value is less than 0.05, it is concluded that the R correlation and the unit matrix in the covariance matrix are different from each other (in any matrix all values except the ones in the diagonal are zero). This means that the factor structure can be subtracted from the correlation matrix, but if the significance value is greater than 0.05, it is interpreted that "there is no shared variance in the matrix" and the factor analysis cannot be performed for the data set (Şencan, 2005). In our analysis, when the Barlett test results were examined, it was found that the obtained chi-square value was significant ($\chi^2_{(3)}$=240.817: p<.0001). In this vein, it is accepted that the variables involved in factor analysis are appropriate for analysis.

Table-4. Anti-image Matrix.

		Weighted-Degree	Betweenness_Centrality	Degree
Anti-image Covariance	Weighted_ Degree	0,199	-0,048	-0,108
	Betweenness_Centrality	-0,048	0,236	-0,099
	Degree	-0,108	-0,099	0,152
Anti-image Correlation	Weighted_ Degree	**,770[a]**	-0,222	-0,622
	Betweenness_Centrality	-0,222	**,815[a]**	-0,523
	Degree	-0,622	-0,523	**,700[a]**

a. Measures of Sampling Adequacy (MSA).

When we look at the anti-image correlation coefficients in Table 4, we see that all the values are greater than 0.5. This shows us that the variables are chosen correctly, and that sample size is sufficient. As a result of the factor analysis, three variables were combined into one component. According to Table 5, the explained variance value was found as 90.611%. This is a pretty good value for centrality. It is also seen that the internal consistency value is 0.66 and combinable. Thus, three variables were combined to obtain a centrality component. The square of the factor loadings gives the percentage of explained variance of this component. (0.966 * 0.966) + (0.949 * 0.949) + (0.941 * 0.941) = 2.718 see Table 6.

Table-5. Factor Loadings.

Variables	One Component			
	Factor Loadings	% of Variance Description	Nonaddivity	Cronbach's Alpha
Degree	0,966		F=1036,525116	
Weighted_Degree	0,949		p=0,0001	0,66
Betweenness_Centrality	0,941	90,61%	Addivity	

Table-6. Total Explained Variance.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,718	90,611	90,611	2,718	90,611	90,611
2	0,181	6,025	96,636			
3	0,101	3,364	100			

Extraction Method: Principal Component Analysis.

3.2. Obtaining Scores with Subjective Scales

Suppose that the average relative network metrics of a footballer during a season is as follow;

Degree = 39

Weighted degree = 148

Betweenness centrality = 28.3906

Eccentricity = 2

Squares of Network Measures' factor loadings, shown in Table 5, are used.

39 x 0.933 + 148 x 0.9006 + 28.3906 x 0.8854 + 1x2 = 36.387 + 133.2888 +25.1370 + 2 =196.8128

Assuming that a footballer scores 23 goals, 10 assists and with the subjective weighting for goals and assists (30% + 10%):

Number of goals x ratio = 23 x 0.30 = 6.9

Number of assists x ratio = 10 x 0.10 =1.0

Total: 6.9 + 1.0 = 7.9

Overall SUM: 196.8128 + 7.9 = 204.7128 is found.

Given the importance of the age factor in transfers, by dividing the overall sum to the age , we get a larger transfer score for young people. For example, if the age of the same footballer is 27, his transfer score will be found as:

204.7128 / 27 = 7.58

However, if the overall sum was calculated for a 30 year old footballer, his transfer score will be

204.7128 0 = 6.82

3.3. Converting the Scores to 0-100 Range and Value

We can convert the transfer scores obtained for a large number of footballers to the range 0-100 with the help of the R following formula

f(x) = (x-min) / (max-min)

> x= c (10, 40, 567, 282, 30)

>xnew= (x-10) / (567-10)

>xnew

(1) 0.00000000 0.05385996 1.00000000 0.48833034 0.03590664

For conversion to the monetary value, a monetary value which is accepted as benchmark, corresponds to the transfer score can be used. Based on this relationship other monetary value of a different transfer can be calculated.

4. DISCUSSION AND CONCLUSION

The sports clubs in our country are in debts and it is obvious that the managerial system is one of the reasons of these loans. Measuring the transfer values of footballers with objective metrics; can help the management system to be based on data rather than rumors over time. Although we do not expect this change to take place soon, the rapid development in technology tells us that it will not take that long. There are developments that confirm this. For example, Carlton's manager Karl Robinson uses video recordings made with drone during training sessions to train his footballers.

Robinson says, "My daughter, aged 11, teaches me how to use the tablet, not just football, but society learns in different ways and we have to keep up with the times" (Smith, 2018). In our article, in which we use programs such Gephi, SPSS and R, we calculate the transfer value of a soccer player by using metrics obtained only from the pass nets produced in the matches, scored goals, assists and as the only non-performance factor: age of the player, which is very important in the transfers.

For further studies other performance or non-performance factors may be included. We are aware that the nets do not reflect the dribbles and are not included in the measurements we have achieved. The network approach we recommend does not see the dribbles as success. In this approach, the situation of the goalkeeper is also another point to be discussed. While the team's aim is to score goal, the goalkeeper's aim is to prevent the goals. For this reason, it is difficult to say that these measures give the success of the goalkeeper. In fact, these words are also valid for the defense. For those who think like this, the flexibility our approach provides is to reduce the weighing of the given subjective weights that we give as 60% (metrics obtained with nets) and 40% (score of goals and assist).

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Contributors/Acknowledgement: All authors contributed equally to the conception and design of the study.

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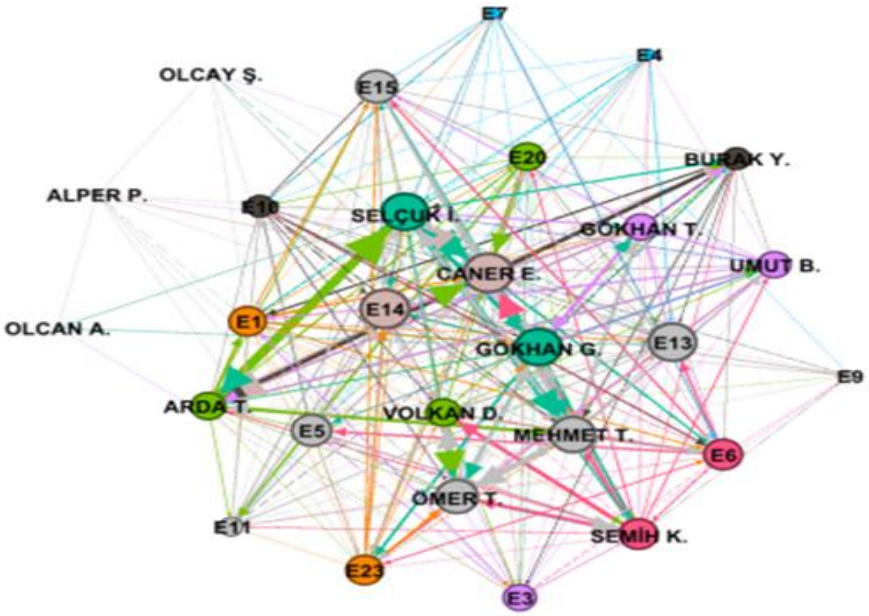
Appendix-1. Obtaining Data

ESTONIA - TURKEY

MATCH SCORE: ESTONIA 0 - 2 TURKEY

MATCH DATE: 11.10.2013-21:30

WORLD CUP 2014 GROUP QUALIFYING MATCH



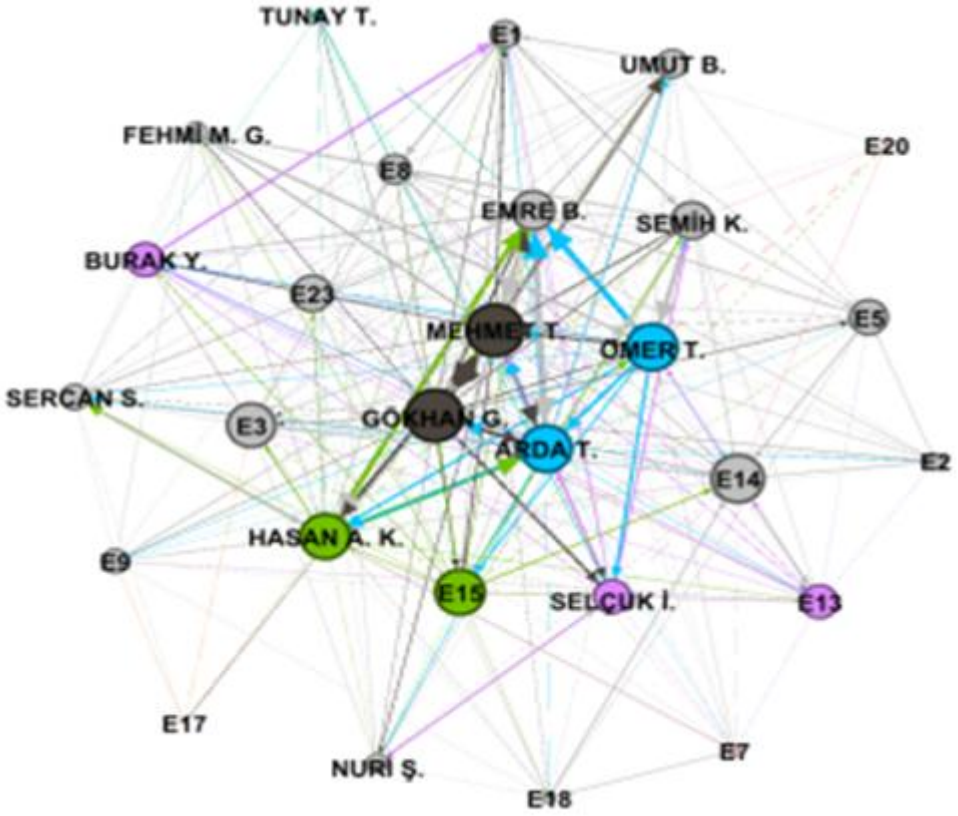
ID	LABEL	IN-DEGREE	OUT-DEGREE	DEGREE	WEIGHTED IN	WEIGHTED OUT	WEIGHTED DEGREE	CLOSENESS CENTRALITY	ECCENTRİCİTY	HARMONIC CLOSENESS CENTRALITY	BETWEENNESS CENTRALITY	PAGERANK
E14	E14	22	20	42	48	50	98	0.794117647	2	0.87037037	24.27411477	0.052596253
E4	E4	7	8	15	10	10	20	0.586956522	2	0.648148148	1.499776612	0.017509897
E20	E20	17	14	31	31	31	62	0.675	2	0.759259259	6.766133866	0.040751664
T20	CANER E.	21	21	42	85	85	170	0.818181818	2	0.888888889	22.5982129	0.050950751
T2	SEMİH K.	17	17	34	53	53	106	0.72972973	2	0.814814815	10.75242951	0.042396324
E5	E5	18	17	35	34	34	68	0.72972973	2	0.814814815	16.0964258	0.042844996
T1	VOLKAN D.	14	17	31	40	40	80	0.72972973	2	0.814814815	10.97096792	0.034689213
T17	BURAK Y.	11	15	26	35	34	69	0.692307692	2	0.777777778	2.57744339	0.027870575
T8	SELÇUK İ.	22	18	40	87	87	174	0.75	2	0.833333333	41.26566905	0.055549186
E15	E15	21	15	36	40	40	80	0.692307692	2	0.777777778	13.4632659	0.049593563
T11	GÖKHAN T.	14	16	30	43	43	86	0.710526316	2	0.796296296	4.655318293	0.034183968
T7	GÖKHAN G.	21	19	40	67	67	134	0.771428571	2	0.851851852	40.7010989	0.053035439
E13	E13	20	21	41	40	40	80	0.818181818	2	0.888888889	27.22894189	0.0484885
E1	E1	15	18	33	33	33	66	0.75	2	0.833333333	17.72569098	0.037578675
T15	MEHMET T.	21	18	39	70	70	140	0.75	2	0.833333333	22.38841436	0.050322527
T9	UMUT B.	13	17	30	34	33	67	0.72972973	2	0.814814815	10.76912116	0.032464067
E23	E23	17	16	33	37	37	74	0.710526316	2	0.796296296	15.86874514	0.041130462
T21	ÖMER T.	16	21	37	63	63	126	0.818181818	2	0.888888889	14.70463703	0.039261938
E6	E6	17	17	34	39	38	77	0.72972973	2	0.814814815	13.09245893	0.040720928
E10	E10	12	14	26	23	24	47	0.675	2	0.759259259	8.237695638	0.031290444
E11	E11	12	11	23	24	24	48	0.627906977	2	0.703703704	3.055999556	0.02932546
T14	ARDA T.	16	15	31	67	67	134	0.692307692	2	0.777777778	5.407736708	0.038976224
E3	E3	15	15	30	21	21	42	0.692307692	2	0.777777778	17.26662782	0.034804858
E9	E9	7	7	14	9	9	18	0.574468085	2	0.62962963	1.078113553	0.017203163
E7	E7	7	8	15	11	11	22	0.574468085	3	0.641975309	0.90297619	0.018395076
T10	OLCAY Ş.	5	4	9	5	5	10	0.509433962	3	0.555555556	1.391666667	0.013191951
T6	ALPER P.	5	6	11	6	6	12	0.551020408	3	0.604938272	4.176984127	0.013209836
T16	OLCAN A.	4	2	6	4	4	8	0.473684211	3	0.50617284	0.083333333	0.01166406

TURKEY – ESTONIA

MATCH SCORE: TURKEY 3 - 0 ESTONIA

MATCH DATE: 11.09.2012-21:00

WORLD CUP 2014 GROUP QUALIFYING MATCH



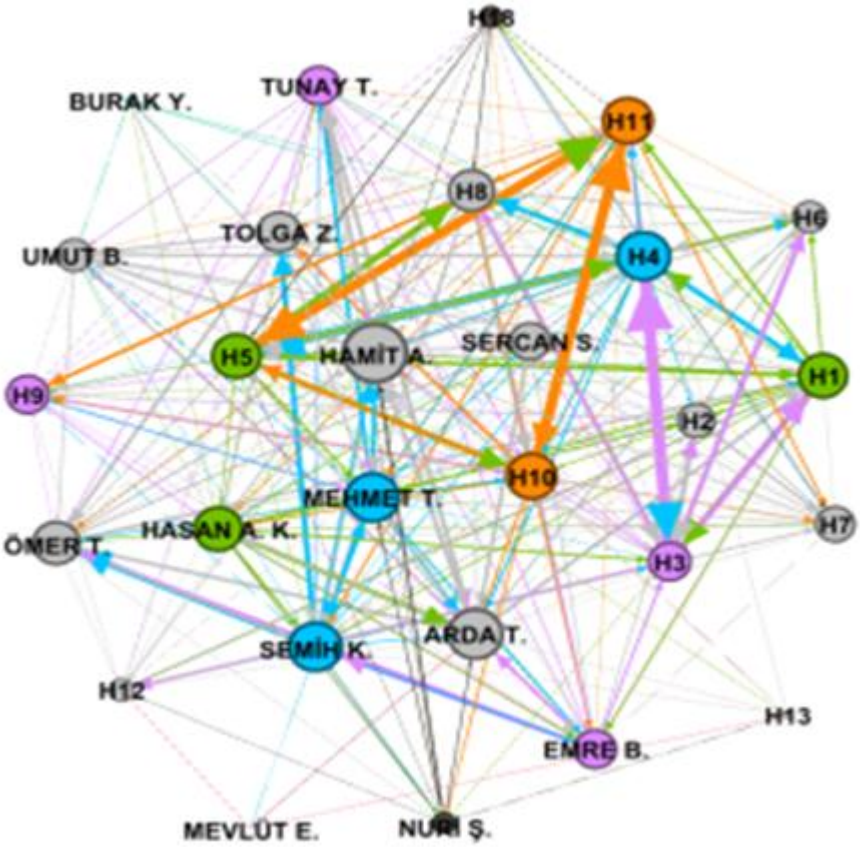
ID	LABEL	IN-DEGREE	OUT-DEGREE	DEGREE	WEIGHTED IN-DEGREE	WEIGHTED OUT-DEGREE	WEIGHTED DEGREE	ECCENTRİCİTY	CLOSENESS CENTRALITY	HARMONIC CLOSENESS CENTRALITY	BETWEENNESS CENTRALITY	PAGERANK
T17	BURAK Y.	15	15	30	37	38	75	2	0.692307692	0.777777778	9.211051345	0.038673713
T5	EMRE B.	18	16	34	96	95	191	2	0.710526316	0.796296296	14.99668691	0.04492767
T3	HASAN A. K.	22	17	39	74	74	148	2	0.72972973	0.814814815	28.39061871	0.05633647
T15	MEHMET T.	23	21	44	116	116	232	2	0.818181818	0.888888889	46.1557516	0.05891858
T9	UMUT B.	12	14	26	37	36	73	2	0.675	0.759259259	2.436602695	0.031317595
T21	ÖMER T.	22	18	40	80	80	160	2	0.75	0.833333333	29.51691488	0.058043333
T14	ARDA T.	18	22	40	96	96	192	2	0.84375	0.907407407	18.09399238	0.045504713
T7	GÖKHAN G.	22	22	44	92	92	184	2	0.84375	0.907407407	33.65629999	0.054547169
E23	E23	16	16	32	25	25	50	2	0.710526316	0.796296296	16.30816257	0.040614449
E13	E13	16	14	30	32	32	64	2	0.675	0.759259259	8.347052698	0.040641056
E9	E9	12	11	23	15	15	30	2	0.627906977	0.703703704	8.622982689	0.030064605
T4	SEMİH K.	17	16	33	53	53	106	2	0.710526316	0.796296296	14.35736892	0.044414186
E5	E5	16	15	31	31	31	62	2	0.692307692	0.777777778	7.805514193	0.040077965
T12	FEHMİ M. G.	12	8	20	24	24	48	3	0.574468085	0.641975309	3.302820279	0.030635248
E3	E3	19	19	38	36	36	72	2	0.771428571	0.851851852	28.72313656	0.048864265
E8	E8	12	15	27	31	31	62	2	0.692307692	0.777777778	6.345128337	0.031491036
E15	E15	18	21	39	42	42	84	2	0.818181818	0.888888889	28.72240717	0.044643041
E14	E14	19	22	41	46	46	92	2	0.84375	0.907407407	34.28566409	0.050084759
E1	E1	12	13	25	40	40	80	2	0.658536585	0.740740741	9.170510922	0.029834881
T23	SERCAN S.	10	14	24	32	32	64	2	0.675	0.759259259	8.097439957	0.027874807
E17	E17	2	3	5	3	3	6	3	0.5	0.537037037	0	0.006342458
E2	E2	8	9	17	16	17	33	3	0.586956522	0.660493827	0.91945179	0.021288887
E18	E18	8	6	14	12	13	25	3	0.551020408	0.604938272	1.597161172	0.020587681
E7	E7	7	6	13	10	10	20	3	0.551020408	0.604938272	1.112373737	0.018711608
T8	SELÇUK İ.	14	16	30	50	49	99	2	0.710526316	0.796296296	11.50027601	0.036340635
T11	TUNAY T.	5	7	12	9	9	18	2	0.574468085	0.62962963	0.518686869	0.014222391
E20	E20	3	3	6	3	3	6	3	0.509433962	0.543209877	0.16025641	0.008397879
T10	NURİ Ş.	10	9	19	21	21	42	2	0.6	0.666666667	4.645687135	0.02659892

NETHERLANDS - TURKEY

MATCH SCORE: NETHERLANDS 2 - 0 TURKEY

MATCH DATE: 07.09.2012-20:30

WORLD CUP 2014 GROUP QUALIFYING MATCH



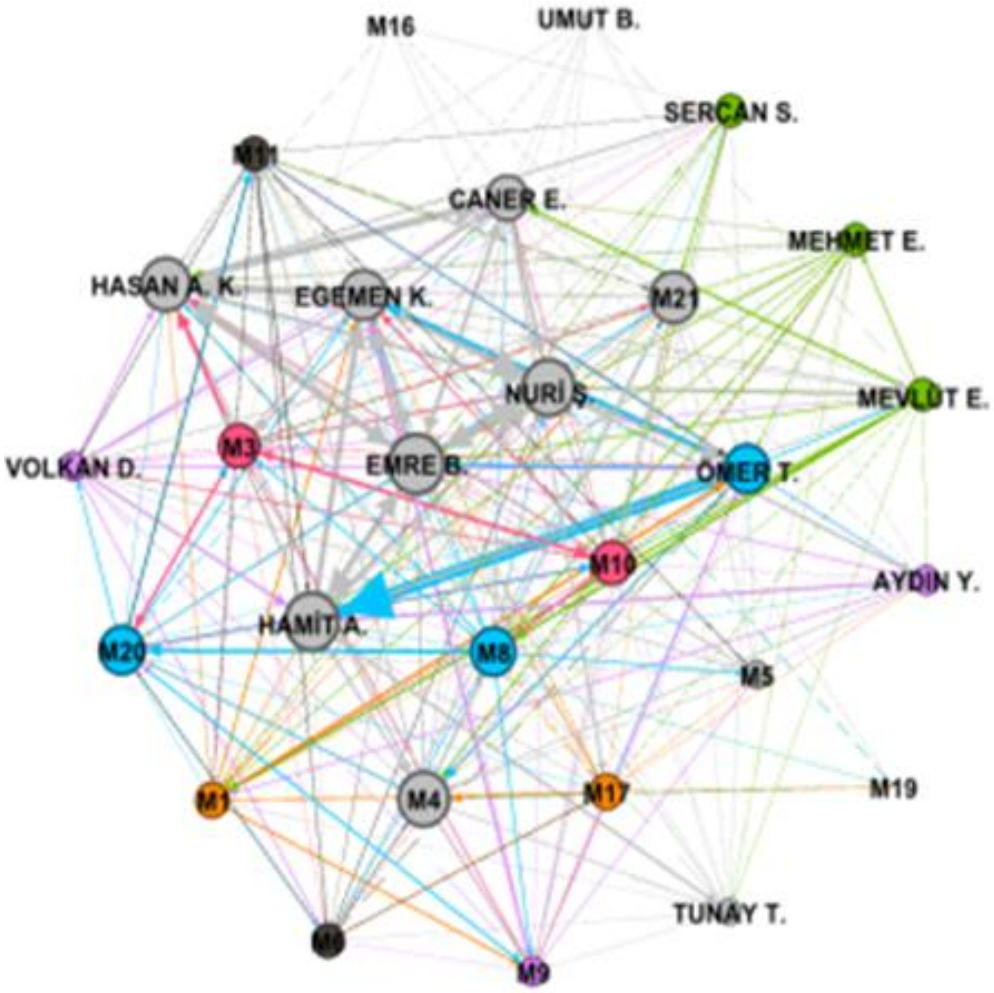
ID	LABEL	IN-DEGREE	OUT-DEGREE	DEGREE	WEIGHTED IN-DEGREE	WEIGHTED OUT-DEGREE	WEIGHTED DEGREE	ECCENTRICITY	CLOSENESS CENTRALITY	HARMONIC CLOSENESS CENTRALITY	BETWEENNESS CENTRALITY	PAGERANK
T9	UMUT B.	12	15	27	25	26	51	2	0.692307692	0.777777778	8.541133866	0.03046076
T21	ÖMER T.	16	18	34	39	39	78	2	0.75	0.833333333	9.669893995	0.03954309
T5	EMRE B.	17	14	31	37	38	75	2	0.675	0.759259259	6.389449439	0.04098645
T4	SEMİH K.	20	18	38	49	49	98	2	0.75	0.833333333	15.83570596	0.04825958
T3	HASAN A. K.	18	17	35	35	35	70	2	0.72972973	0.814814815	17.03855589	0.04327324
H2	H2	14	14	28	29	29	58	2	0.675	0.759259259	5.244305694	0.03405635
T14	ARDA T.	19	20	39	57	57	114	2	0.794117647	0.87037037	51.37014652	0.04605767
H8	H8	16	17	33	42	42	84	2	0.72972973	0.814814815	12.86628927	0.03941851
T11	TUNAY T.	15	16	31	32	32	64	2	0.710526316	0.796296296	7.400391275	0.03682624
H1	H1	15	20	35	49	49	98	2	0.794117647	0.87037037	13.5982129	0.03746216
H4	H4	20	18	38	65	65	130	2	0.75	0.833333333	16.79983627	0.04812873
H6	H6	13	13	26	34	34	68	2	0.658536585	0.740740741	3.612129537	0.0315265
H3	H3	16	15	31	60	60	120	2	0.692307692	0.777777778	9.413908314	0.03900059
H11	H11	18	18	36	56	56	112	2	0.75	0.833333333	15.02332112	0.04383511
H10	H10	18	18	36	52	52	104	2	0.75	0.833333333	14.18744034	0.04359965
H7	H7	13	16	29	24	23	47	2	0.710526316	0.796296296	8.332184482	0.03202242
T15	MEHMET T.	20	18	38	48	48	96	2	0.75	0.833333333	23.71146076	0.04744239
T23	SERCAN S.	16	14	30	26	26	52	2	0.675	0.759259259	5.607714508	0.03828899
T1	TOLGA Z.	16	16	32	32	32	64	2	0.710526316	0.796296296	20.46113054	0.03930532
T6	HAMİT A.	24	21	45	62	62	124	2	0.818181818	0.888888889	37.93437951	0.05714866
H5	H5	19	16	35	63	63	126	2	0.710526316	0.796296296	15.28677711	0.04502556
H9	H9	15	16	31	25	24	49	2	0.710526316	0.796296296	7.957592408	0.03655365
H12	H12	10	10	20	15	15	30	2	0.613636364	0.685185185	10.39215784	0.02411637
H18	H18	10	9	19	12	12	24	3	0.586956522	0.660493827	1.707464757	0.02468483
T17	BURAK Y.	4	5	9	5	5	10	3	0.54	0.586419753	0.908730159	0.01122719
T10	NURİ Ş.	9	10	19	14	14	28	2	0.613636364	0.685185185	7.960989011	0.02213707
T19	MEVLÜT E.	2	3	5	3	3	6	3	0.5	0.537037037	0.361111111	0.00647677
H13	H13	5	5	10	5	5	10	3	0.54	0.586419753	4.387587413	0.01313615

HUNGARY-TURKEY

MATCH SCORE: HUNGARY 3 - 1 TÜRKİYE

MATCH DATE: 10-2013-20:30

WORLD CUP 2014 GROUP QUALIFYING MATCH



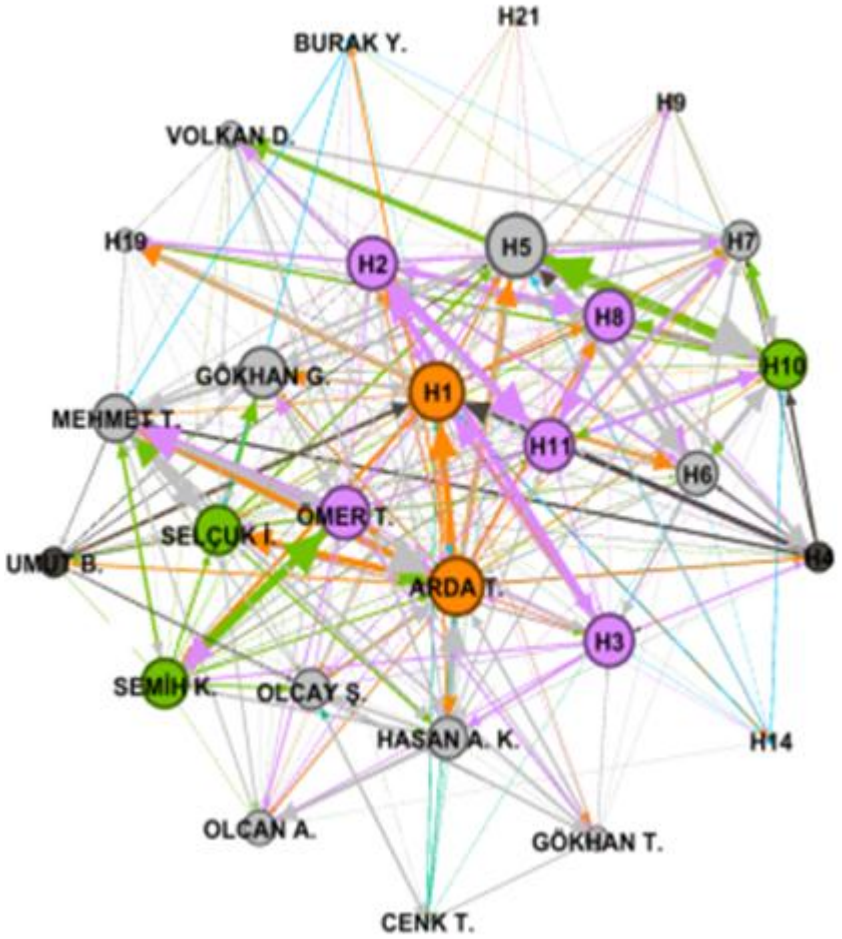
ID	LABEL	IN-DEGREE	OUT-DEGREE	DEGREE	WEIGHTED IN-DEGREE	WEIGHTED OUT-DEGREE	WEIGHTED D	ECCENTRICITY	CLOSENESS CENTRALITY	HARMONIC CLOSENESS CENTRALITY	BETWEENNESS CENTRALITY	PAGERANK
20	NURİ Ş.	20	19	39	86	89	175	2	0.771428571	0.851851852	40.31990715	0.050736558
21	EMRE B.	21	20	41	91	91	182	2	0.794117647	0.87037037	28.31058246	0.053055047
18	HASAN A. K.	18	19	37	83	82	165	2	0.771428571	0.851851852	26.67625567	0.04901005
16	EGEMEN K.	16	19	35	84	84	168	3	0.75	0.845679012	16.08807844	0.042813518
19	ÖMER T.	19	15	34	63	63	126	2	0.692307692	0.777777778	17.34213285	0.049225046
15	M1	15	11	26	26	26	52	3	0.613636364	0.697530864	5.936764624	0.038362591
17	M10	17	14	31	39	38	77	3	0.658536585	0.75308642	10.68112304	0.045362385
15	M3	15	16	31	44	44	88	3	0.692307692	0.790123457	21.99529311	0.040391308
19	HAMİT A.	19	21	40	81	81	162	2	0.818181818	0.888888889	33.34283326	0.048128593
16	CANER E.	16	16	32	54	54	108	2	0.710526316	0.796296296	11.06630257	0.040828963
17	M8	17	17	34	39	39	78	2	0.72972973	0.814814815	15.67744006	0.043974413
13	M11	13	12	25	24	23	47	2	0.642857143	0.722222222	6.871923354	0.032820229
21	M4	21	17	38	49	49	98	2	0.72972973	0.814814815	31.75152792	0.053633444
11	MEVLÜT E.	11	13	24	31	31	62	2	0.658536585	0.740740741	7.453694916	0.028951414
19	M21	19	17	36	38	38	76	2	0.72972973	0.814814815	22.75665666	0.048843985
9	M9	9	13	22	26	25	51	3	0.642857143	0.734567901	5.405660728	0.024848699
12	M6	12	13	25	21	21	42	2	0.658536585	0.740740741	7.473903874	0.030979578
12	M17	12	14	26	21	21	42	2	0.675	0.759259259	26.46483877	0.031574961
8	TUNAY T.	8	12	20	15	15	30	3	0.627906977	0.716049383	3.306991619	0.021525678
11	VOLKAN D.	11	11	22	27	27	54	3	0.613636364	0.697530864	3.797337793	0.029491369
17	M20	17	17	34	43	44	87	2	0.72972973	0.814814815	13.30905289	0.045586479
11	MEHMET E.	11	13	24	21	21	42	3	0.642857143	0.734567901	4.773373848	0.027521469
11	M5	11	10	21	16	16	32	3	0.6	0.679012346	5.745646021	0.029183441
10	AYDIN Y.	10	12	22	24	24	48	2	0.642857143	0.722222222	6.559210789	0.026785335
14	SERCAN S.	14	10	24	19	19	38	3	0.6	0.679012346	10.94153675	0.036711217
5	UMUT B.	5	5	10	5	5	10	3	0.54	0.586419753	0.498611111	0.013212888
2	M19	2	3	5	3	3	6	3	0.519230769	0.549382716	3.286436603	0.006938157
3	M16	3	3	6	3	3	6	3	0.465517241	0.512345679	5.166883117	0.009503185

TURKEY- NETHERLANDS

MATCH SCORE: TURKEY 0 - 2 NETHERLANDS

MATCH DATE: 15.10.2013-21:00

WORLD CUP 2014 GROUP QUALIFYING MATCH



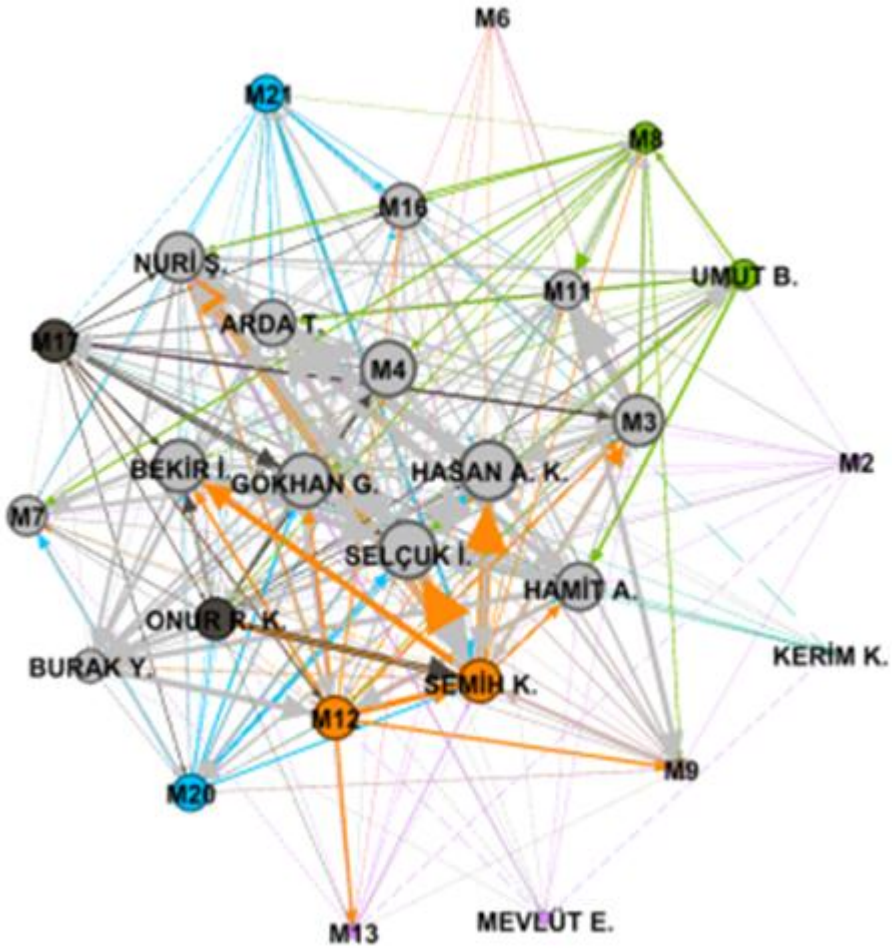
ID	LABEL	IN-DEGREE	OUT-DEGREE	DEGREE	WEIGHTED IN-DEGREE	WEIGHTED OUT-DEGREE	WEIGHTED DEGREE	ECCENTRICITY	CLOSENESS CENTRALITY	HARMONIC CLOSENESS CENTRALITY	BETWEENNESS CENTRALITY	PAGERANK
H9	H9	7	8	15	11	12	23	2	0.586956522	0.648148148	0.840280961	0.017956728
H10	H10	19	16	35	58	57	115	2	0.710526316	0.796296296	23.82485837	0.046589041
H8	H8	18	19	37	46	45	91	2	0.771428571	0.851851852	13.07899729	0.044240989
H6	H6	18	14	32	47	47	94	2	0.675	0.759259259	17.45544306	0.045329636
H4	H4	14	10	24	29	29	58	2	0.613636364	0.685185185	2.68952061	0.0359941
H5	H5	23	20	43	66	66	132	2	0.794117647	0.87037037	42.30935315	0.057713735
T7	GÖKHAN G.	18	18	36	45	45	90	2	0.75	0.833333333	27.85112516	0.045205805
H1	H1	18	22	40	61	61	122	2	0.84375	0.907407407	39.98319083	0.048403874
H7	H7	14	15	29	39	39	78	2	0.692307692	0.777777778	11.50742303	0.035532143
H2	H2	18	19	37	56	56	112	2	0.771428571	0.851851852	13.57868649	0.042910315
H11	H11	18	19	37	48	47	95	2	0.771428571	0.851851852	19.49316645	0.0434196
T14	ARDA T.	20	20	40	75	75	150	2	0.794117647	0.87037037	29.26900034	0.050767535
T3	HASAN A. K.	17	14	31	42	42	84	2	0.675	0.759259259	13.60657625	0.039623218
T8	SELÇUK İ.	19	16	35	49	50	99	2	0.710526316	0.796296296	12.04006498	0.046977669
T16	OLCAN A.	12	15	27	24	24	48	2	0.692307692	0.777777778	7.066918681	0.030617123
T17	BURAK Y.	6	5	11	8	9	17	2	0.551020408	0.592592593	0.875505051	0.016462603
T21	ÖMER T.	19	18	37	52	52	104	2	0.75	0.833333333	18.56298373	0.046680923
T15	MEHMET T.	17	17	34	64	64	128	2	0.72972973	0.814814815	13.80201594	0.043089027
T2	SEMİH K.	16	19	35	42	42	84	2	0.771428571	0.851851852	14.94681193	0.039486269
T9	UMUT B.	12	12	24	20	20	40	2	0.642857143	0.722222222	3.278931668	0.029450544
H3	H3	21	16	37	43	43	86	2	0.710526316	0.796296296	11.80294001	0.052050629
T1	VOLKAN D.	8	14	22	23	23	46	2	0.675	0.759259259	2.471001118	0.01952888
H14	H14	6	5	11	9	9	18	3	0.54	0.586419753	0.523892774	0.016173074
H19	H19	7	13	20	23	23	46	2	0.658536585	0.740740741	0.877761025	0.017887132
T10	OLCAY Ş.	17	13	30	32	32	64	2	0.658536585	0.740740741	12.73099807	0.041069157
T11	GÖKHAN T.	9	12	21	22	22	44	2	0.642857143	0.722222222	3.823200411	0.023710515
T20	CENK T.	4	6	10	10	10	20	2	0.5625	0.611111111	0.565811966	0.011460759
H21	H21	4	4	8	4	4	8	3	0.529411765	0.567901235	0.14354067	0.011668978

TURKEY-HUNGARY

MATCH SCORE: TURKEY 1 - 1 HUNGARY

MATCH DATE: 26.03.2013-20:30

WORLD CUP 2014 GROUP QUALIFYING MATCH



ID	LABEL	IN-DEGREE	OUT-DEGREE	DEGREE	WEIGHTED IN-DEGREE	WEIGHTED OUT-DEGREE	WEIGHTED DEGREE	ECCENTRICITY	CLOSENESS CENTRALITY	HARMONIC CLOSENESS CENTRALITY	BETWEENNESS CENTRALITY	PAGERANK
M11	M11	16	14	30	39	40	79	2	0.684210526	0.769230769	15.05379522	0.039269439
M21	M21	15	14	29	23	23	46	2	0.684210526	0.769230769	3.493767344	0.038795252
T3	HASAN A. K.	23	20	43	77	77	154	2	0.8125	0.884615385	30.28925328	0.056426151
M20	M20	15	14	29	32	33	65	2	0.684210526	0.769230769	3.192525938	0.037365939
T6	HAMİT A.	17	19	36	57	57	114	2	0.787878788	0.865384615	13.82770835	0.043025822
T17	BURAK Y.	11	16	27	45	45	90	2	0.722222222	0.807692308	6.491097791	0.029069616
T14	ARDA T.	16	19	35	60	60	120	2	0.787878788	0.865384615	11.71092796	0.041721126
M4	M4	19	22	41	48	48	96	2	0.866666667	0.923076923	20.15844711	0.049146864
T8	SELÇUK İ.	20	22	42	94	94	188	2	0.866666667	0.923076923	24.14287096	0.051038157
T10	NURİ Ş.	21	16	37	68	68	136	2	0.722222222	0.807692308	9.867656363	0.051626344
M12	M12	15	18	33	45	45	90	2	0.764705882	0.846153846	19.31376303	0.037886398
M16	M16	17	17	34	34	34	68	2	0.742857143	0.826923077	11.41951099	0.043537655
T9	UMUT B.	12	13	25	27	27	54	2	0.666666667	0.75	2.017746143	0.03183105
T7	GÖKHAN G.	21	19	40	58	58	116	2	0.787878788	0.865384615	26.43459776	0.051570564
T2	BEKİR İ.	21	18	39	48	48	96	2	0.764705882	0.846153846	16.43795458	0.051507867
T4	SEMİH K.	17	16	33	70	70	140	2	0.722222222	0.807692308	17.73957981	0.042357496
T23	ONUR R. K.	17	15	32	32	32	64	2	0.702702703	0.788461538	9.423132423	0.043467791
M8	M8	13	12	25	27	27	54	2	0.65	0.730769231	5.061623507	0.032473712
M3	M3	21	17	38	56	56	112	2	0.742857143	0.826923077	34.34285894	0.053064207
M17	M17	17	15	32	34	34	68	2	0.702702703	0.788461538	7.675641896	0.041894801
M9	M9	7	12	19	24	24	48	2	0.65	0.730769231	3.293093889	0.018088445
M7	M7	16	15	31	32	32	64	2	0.702702703	0.788461538	10.48535811	0.040276808
M2	M2	6	8	14	8	8	16	2	0.590909091	0.653846154	2.742229013	0.015959201
M13	M13	7	7	14	10	8	18	2	0.577777778	0.634615385	3.347619048	0.017855184
M6	M6	3	4	7	4	4	8	3	0.530612245	0.570512821	0.226190476	0.009332784
T19	MEVLÜT E.	7	7	14	8	8	16	2	0.577777778	0.634615385	0.953907204	0.017996428
T21	KERİM K.	5	6	11	6	6	12	3	0.541666667	0.602564103	0.857142857	0.0134149